低露出画像に対するノイズを考慮した画像強調法

A noise-aware enhancement method for underexposed images

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Abstract

A new method of contrast enhancement for underexposed images, in which lots of noise are hidden in an image, is proposed in this paper. Under low light conditions, images taken by digital cameras have low contrast in dark or bright regions. This is due to a limited dynamic range that imaging sensors have. For these reasons, various contrast enhancement methods have been proposed so far. These methods, however, have two problems: (1) The loss of details in bright regions due to over-enhancement of contrast. (2) The noise is amplified in dark regions because they do not consider noise included images. The proposed method overcomes these problems by using the shadow-up function is applied to adaptive gamma correction with weighting distribution. A denoising filter is also used to avoid noise being amplified in dark regions. As a result, it is concluded that the proposed method allows not only to enhance contrast of dark region, but also to avoid amplifying noise, even under strong noise environments.

1 INTRODUCTION

The low dynamic range (LDR) of modern digital cameras are a major factor preventing them from capturing images as well with human vision. This is due to a limited dynamic range which imaging sensors have. For this reason, images taken by digital cameras have low contrast in dark or bright regions. To overcome the problem, various contrast enhancement methods have been proposed so far.

The histogram equalization (HE) is one of the most popular algorithms for contrast enhancement and there are various extended versions of the HE. However, these histograms-based methods cause the loss of details in bright regions due to over-enhancement of contrast. In addition, most of the conventional methods amplify noise in dark regions, because they do not consider noise included images. On the other hand, contrast enhancement methods based on the retinex theory have also been studied. Although these methods can enhance the contrast while preserving details in bright areas, they also cause the noise amplifying as with histogram-based methods.

To avoid the noise amplification, some histogram-based contrast enhancement methods have been proposed. Low light image enhancement based on two-step noise suppression (LLIE) uses both noise level function (NLF) and just noticeable difference (JND) in contrast enhancement for noise suppression. Although this method can reduce some noise, it does not preserve the details in bright areas as with histogram-based methods.

Because of such a situation, this paper aims to enhance the contrast of images that are underexposed and contain noise, while preserving details. In other words, the aim is to improve the quality of images taken by a digital camera in low light environments. In the proposed method, an image is decomposed into illumination layer and reflectance layer based on the Retinex theory for reducing the effect of noise. The lightness information of the illumination layer is adjusted by using adaptive gamma correction with weighting distribution (AGCWD). The shadow-up function is applied to AGCWD to prevent over-enhancement and the loss of details in bright regions. A denoising filter is also used to avoid noise being amplified in dark regions.

In our previous work [1], we presented a framework of contrast enhancement which can avoid over-enhancement and noise amplification. However, the image enhancement is weak when images include strong noise. Because of this, the result just be enhanced slightly under strong noise environments. The retinex theory allows us to obtain real-world scenes from original images [2] such that color is unaffected by reflection, so we use a control factor based on luminance adaptation to reduce the effect of noise on contrast enhancement. We extend our previous work [1] by applying the retinex theory to achieve a more more natural and clearly enhanced image, even under strong noise environments.

We evaluate the effectiveness of the proposed method in terms of the quality of enhanced images by a number of simulations. In the simulations, the proposed method is compared with conventional contrast enhancement methods, including state-of-art ones. Experimental results showed that the proposed method can produce high quality images without over-enhancement, and the proposed method outperforms conventional ones in terms of the noise robustness.

2 Related work

This section summarizes research and technology related to this research.

2.1 Retinex theory

The classic Retinex model decomposes images into reflectance and illumination as $S = R \cdot L$, where S is the observed image, R and L represent the reflectance and the illumination of the image. The operator $\cdot$ denotes the elementwise multiplication.

To filter images need Gauss filter as follow

$$R(x, y) = \log I(x, y) - \log[F(x, y) * I(x, y)] \tag{1}$$

where $I(x, y)$ is the gray scale of the image, $*$ represents the convolution operation, and $F(x, y)$ is the gaussian function:

$$F(x, y) = Ke^{\frac{-(x^2+y^2)}{c^2}} \tag{2}$$

In the gaussian function, $x^2 + y^2$ is the distance from the center point, while c is a constant to determine the range of the Gauss function. In addition, K is a constant, which satisfies the following:

$$\iint F(x, y)dxdy = 1 \tag{3}$$

The range of c value determines the result of Gauss function, and affects the processing of Retinex algorithm. When c value is larger, the range of pixels is larger, and more color information can be preserved. On the other hand, when c value is smaller, the range of pixels is smaller. Although the edge information on the image can be strengthened, the color information is lost. Because of this situation, Multi Scale Retinex (MSR) algorithm is generated to improve Single Scale Retinex (SSR).

Because the SSR cannot preserve both color and edge information, MSR algorithm has been developed. Woodell proposed a new algorithm called Multiple-Scale Retinex (MSR), which uses different scales of Gauss functions. It works by giving different weights and different sizes of Gaussian functions, while preserving the edge and color information of the image. Each Gauss function gives different weights, and the sum of weights is equal to 1. In this way, the shortcomings of SSR algorithm caused by c value are improved. Small Gauss function preserves image edge information and large Gauss function preserves image color information. Both edge information and color information can be preserved.

$$R(x,y) = \sum_{K=1}^{K} W_k(logI(x,y) - log[F(x,y) * I(x,y)]) \tag{4}$$

As shown in above, where W_k represents the weight value of the Kth of SSR, and $F(x,y)$ is a Gaussian function. Each Gauss function multiplies by its own weight value and sum up.

$$R_{MSR}(x,y) = \sum_{K=1}^{K} W_k R_{SSR}(x,y) \tag{5}$$

MSR deals with grayscale images. If the color image is processed by Retinex, the RGB three color channel must be processed separately. Each channel is enhanced separately, and then the information of the three channels is combined for output. However, after combining the three RGB channels to output images, some problems arise as follows:

1. It may not be able to show correct colors.
2. Decrease the saturation of the whole image.
3. If the original image has color distortion problem, the color distortion is more serious after doing MSR.

4. Halo effect.

5. When do image enhancement, the noise in the dark or shadows also be enhanced.

Because the disadvantage of MSR is that it cannot preserve the original color information, Multi Scale Retinex with color Restoration (MSRCR) has been proposed. The concept is to consider the RGB information of the original image, and then adjust the results of MSR. After doing MSR, the RGB information is pulled back to the RGB information of the original image, such as following:

$$R'_{MSR_I} = R_{MSR_I} \times I'_i(x, y) \tag{6}$$

where I' is given by the following

$$I'_i(x, y) = \beta log(\alpha \frac{I_i(x, y)}{\sum_{i=3}^{3} I_i(x, y)}) \tag{7}$$

In this equation, $I'_i(x, y)$ represents the pixel values of R, G and B, while α and β are constants. Although MSRCR has adjusted the value of RGB, it is still unable to approximate the color information of the original image.

Different from conventional variational models, a weighted variational model for simultaneously estimating reflectance and illumination has been proposed. This model can preserve the estimated reflectance with more details. Moreover, the proposed model can suppress noise to some extent.

Based on the widely used assumptions, a new objective function is established by weighting the regularization terms:

$$E(r, l) = ||r + l - s||_2^2 + c_1||e^r \cdot \nabla r||_1 + c_2||e^l \cdot \nabla l||_2^2 \tag{8}$$

where c_1 and c_2 are positive parameters,$|| \quad ||_p$ denotes the p-norm operator. To minimize $E(r, l)$, for the first term ($||r+l-s||_2^2$)), which corresponds to L2 data fidelity, is to minimize the distance between estimated $(r + l)$ and observed image s. The second term ($||e^r \cdot \nabla r||_1$)), which corresponds to TV reflectance sparsity, enforces piecewise constant on the reflectance r. The third term ($||e^l \cdot \nabla l||_2^2$) enforces spatial smoothness on the illumination l.

2.2 Image Enhancement

The histogram equalization (HE) [3] is one of the most popular algorithms for contrast enhancement [5] and various extended versions of the HE have been proposed [4, 6–8]. Brightness preserving bi-histogram equalization (BBHE) [6] enhances the contrast by using partitioned histogram based on the mean value of an image. Similarly, dualistic sub-image histogram equalization (DSIHE) [7] uses histograms which are partitioned by the median value of an image. Contrast accumulated histogram equalization for image enhancement [8] enhances the image by using visual importance estimation and histogram reformulation. Efficient contrast enhancement using adaptive gamma correction with weighting distribution (AGCWD) [4] aims to prevent over-enhancement and under-enhancement caused by the HE by using an adaptive gamma correction and a modified probability distribution. However, there are still issues that the over-enhancement and the loss of contrast in bright areas are caused by these histograms-based methods. Some noise hidden in the darkness is also amplified.

On the other hand, contrast enhancement methods based on the retinex theory have also been studied. For example, retinex-based perceptual contrast enhancement in images using luminance adaptation [15], which utilizes the characteristic of human eye sensitivity, allows not only to enhance the contrast, but also to preserve details in bright areas. However, as well as histogram-based methods, the noise is not considered.

Because of such a situation, some histogram-based contrast enhancement methods preventing the noise amplification have been proposed. In the methods, shrinkage functions are used for preventing the noise amplification. Low light image enhancement based on two-step noise suppression (LLIE) [14] uses both noise level function (NLF) and just noticeable difference (JND) for contrast enhancement with noise suppression. Although this method can reduce some noise, it does not preserve the details in bright areas as with histogram-based methods.

2.3 Denoising filter

Bilateral filter [29]is a kind of non-linear filter, which can keep an edge and reduce noise smoothly. Like other filters, bilateral filter uses weighted averaging method. The intensity of a pixel is represented by the weighted average of the brightness value of the surrounding pixel, and the weighted average is based on the Gauss distribution. Most importantly, the weight of bilateral filtering considers not only the Euclidean distance of the pixel, but also the radiation difference in the range of the pixel. Both weights are taken into account when calculating the central pixel. Although bilateral filter preserves the edge of the image, it removes the texture of the image. It makes the image worse, but it can retain the shadow in the image. For color images, multiple iterations also flatten the color. The original color is mapped to a smaller color space after smoothing.

Median filter [30]is a non-linear smoothing technique, which sets the gray value of each pixel to the median value of all pixels in a neighborhood window of that point. Generally used to deal with salt and pepper noise is mainly based on the fact that the median value is not affected by the maxima and minima of the distribution sequence. When the median filter is used to process images, the edges of images may be contaminated, that is, the edges become blurred. Especially when the neighborhood range of the processing becomes larger, this kind of ambiguity will be more obvious.

The main steps of BM3D [31] are grouping and collaborative filtering. First look at grouping, which is different from other methods using k-means clustering algorithm. Here we use grouping with matching, which is actually the operation: The fragments whose distance from the reference is smaller than a given threshold are considered mutually similar and are subsequently grouped. Then the collaborative filtering, where collaborative filtering is not recommended collaborative filtering. But literally, fragments in each group work together to filter. Previous algorithms, including those based on non-local means, usually mean directly or weighted by similarity after finding similar patches. Collaborative filtering is used here, and the final result is different for each fragment. The implemented method is Collaborative Filtering by Shrinkage in Transform Domain. Firstly, the $D + 1$ dimensional linear transformation is applied to group, then the shrink transform domain coefficients are applied, and then invert. These groups are represented by two types: intrafragment correlation and interfragment correlation. In addition, the method of extending to color image is to convert to YCbCr color space first. Then, using the relatively high SNR characteristic of Y, which is luminance channel, grouping with Y. And suppose the grouping constraint on the chrominances is based on the assumption that if the luminances of two blocks are mutually similar, then their chrominances are also mutually similar.

3 A noise-aware enhancement method

Here, we propose a novel contrast enhancement method with a noise aware shadow-up function. For color images, we use value $V(x, y)$ at pixel(x, y), in the HSV color space, as luminance $l(x, y)$ in accordance with [26]. The outline of the proposed method is shown in Fig 1.

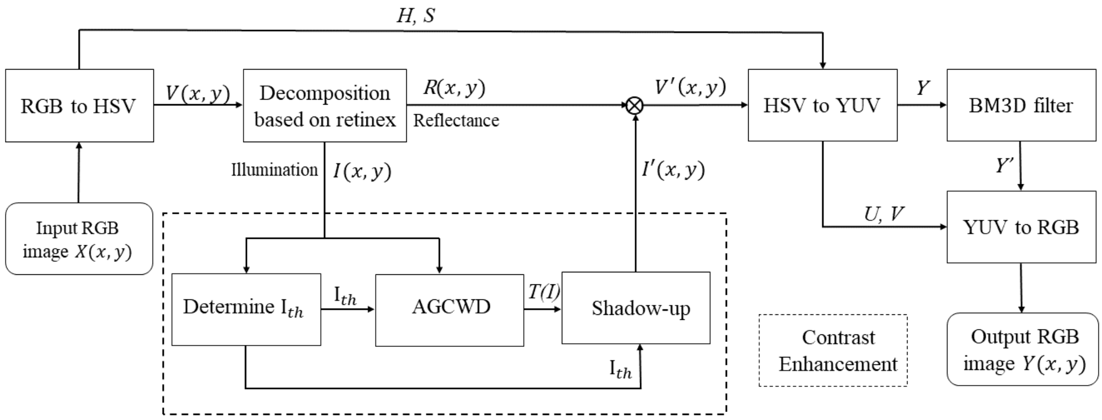


Fig 1: Flowchart of the proposed method.

3.1 Decomposition based on Retinex

As shown in Fig 1, input RBG image $X(x, y)$ is transformed to an HSV image, where $H(x, y), S(x, y)$ and $V(x, y)$ are Hue, Saturation and Value respectively. An excellent weighted variational model (WVM) has been proposed [25] for simultaneous reflectance and illumination estimation. We use this model for decomposing V(x,y) into illumination layer $I(x, y)$ and reflectance layer $R(x, y)$, where $I(x, y)$ includes almost no noise, but $R(x, y)$ includes, due to the work of the model. We can easily understand the advantages of WVM which is shown in Fig 2. Examples of illumination layer and reflectance layer of weighted variational model (WVM) are shown in Fig 3. We use an illumination layer for contrast enhancement.

(a) original image

(b) SSR

(c) MSR

(d) MSRCR

(e) WVM

Fig 2: Examples of retinex algorithm under different methods.

(a) Illumination layer

(b) Reflectance layer

Fig 3: Example of weighted variation model (WVM) with Fig 2a.

3.2 Contrast Enhancement

$$F(I) = \begin{cases} T(I), \text{if } I < I_{th} \\ I, \text{otherwise} \end{cases}, \tag{9}$$

where $I \in [0, 255]$ is the intensity of illumination layer, $T(I)$ is a monotonically increasing function, and I_{th} is the upper limit for the nonlinear

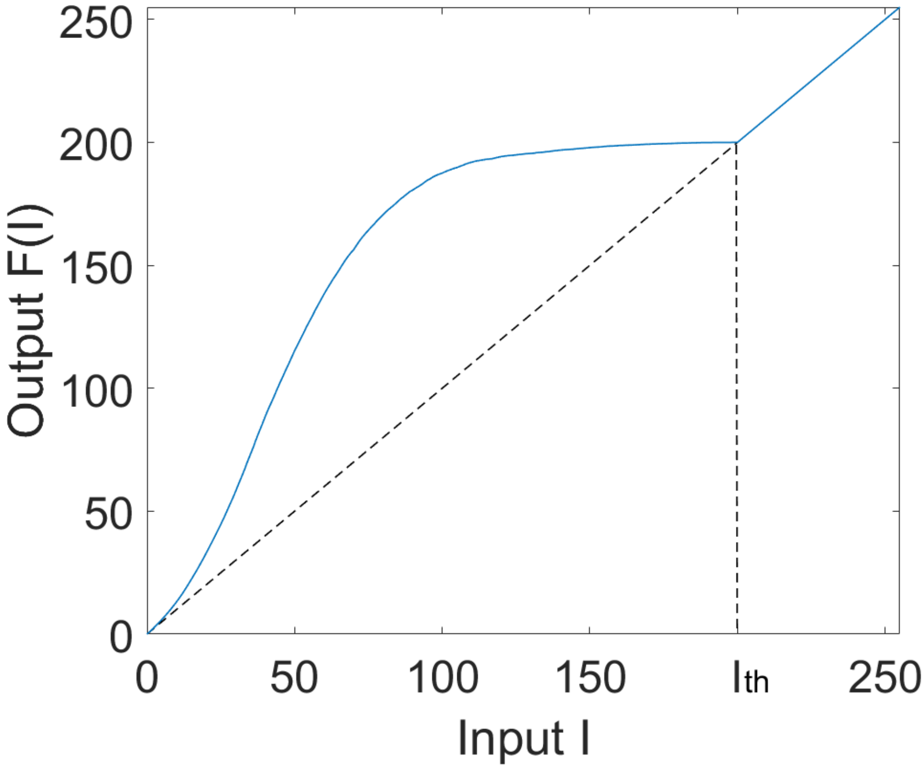


Fig 4: Example of shadow-up function.

part, which is used for avoiding over enhancement in bright areas. Contrast is enhanced only when I is less than the threshold value I_{th}, according to eq. (1).

AGCWD consists of the adaptive gamma correction and the weighting distribution (WD) function. The adaptive gamma correction is formulated as follows:

$$T(I) = I_{max}(I/I_{max})^{1-cdf_w(I)}, \tag{10}$$

where cdf_w is the modified cumulative distribution function (CDF) based on the weighting distribution function. The WD function with adjusted parameter α is formulated as follows:

$$pdf_w(I) = pdf_{max}\left(\frac{pdf(I) - pdf_{min}}{pdf_{max} - pdf_{min}}\right)^{\alpha}, \tag{11}$$

where pdf_{max} and pdf_{min} are the maximum and minimum values of the probability density function pdf, respectively. In this paper, pdf is given as $pdf(I) = n_I/(MN)$, where n_I is the number of pixels that have intensity I and MN is the total number of pixels in the image. The modified CDF cdf_w is calculated as follows:

$$cdf_w(I) = \sum_{I=0}^{I_{max}} pdf_w(I)/\Sigma pdf_w, \tag{12}$$

where the sum of pdf_w is calculated is given by

$$\Sigma pdf_w = \sum_{I=0}^{I_{max}} pdf_w(I). \tag{13}$$

To determine a proper threshold value I_{th} for illumination layer, we take into account the luminance distribution of the illumination layer. Let $H = \{(x, y) : I_{th} < I(x, y) < I_{max}\}$, where I_{th} is the th percentile of luminance $I(x, y)$ of the input image, and I_{max} is the maximum of $I(x, y)$. The threshold value I_{th} is calculated as follows:

$$I_{th} = 255 - \frac{1}{|H|} \sum_{(x,y)\in H} I(x, y), \tag{14}$$

The threshold value I_{th} become smaller for a brighter image, while I_{th} become larger for a darker image. Example of enhanced illumination layer is shown in Fig 5 .

3.3 Output RGB image $Y(x, y)$

By enhancing the illumination layer, an adjusted illumination $I'(x, y)$ is obtained. Then an enhanced $V'(x, y)$ is computed by:

$$V'(x, y) = I'(x, y) \cdot R(x, y) \tag{15}$$

Finally, output RGB image $Y(x, y)$ is obtained by transforming $V'(x, y)$, $H(x, y)$, and $S(x, y)$, according to the model [14].

Fig 5: Example of illumination layer is enhanced by AGCWD with shadow-up function.

3.4 Denoising technique

Possible noises previously hiding in the dark are also accordingly amplified, especially for the very low-light inputs (regions), as shown in Fig10a. Denoising techniques are required to further improve the visual quality. Many off-the-shelf denosing tools, such as [31–33], can be employed to do the job. Considering the comprehensive performance, BM3D [31] is the choice of this work. In our implementation, for further cutting the computational load, we only execute BM3D on the Y channel by converting image $Y(x, y)$ from the RGB colorspace into the YUV one.

3.5 Proposed procedure

The proposed procedure for enhancing an image is summarized as follows (see Fig. 1).

(a) Original image (b) Denoised image

Fig 6: Example of BM3D.

1. Calculate $V(x, y)$ from an input image $X(x, y)$.
2. Decompose $V(x, y)$ into $R(x, y)$ and $I(x, y)$ according to Ref. 25.
3. Determine a threshold value I_{th} by eq. (14).
4. Design $F(I)$ by using AGCWD [4] and I_{th}.
5. Calculate the enhanced luminance $I'(x, y)$ according to eq. (9).
6. Compute $V'(x, y)$ by combining $I'(x, y)$ and $R(x, y)$.
7. Obtain enhanced image $Y(x, y)$ by transforming H, S, and $V'(x, y)$ into the RGB color space.
8. Change the color space of enhanced image $Y(x, y)$ from RGB color space to YUV color space.
9. Execute BM3D [31]on the Y channel and obtain denoising image $Z(x, y)$ by transforming U, V, and processed Y' into the RGB color space.

(a) (b)

Fig 7: Natural images taken by digital camera.

(a) (b) (c)

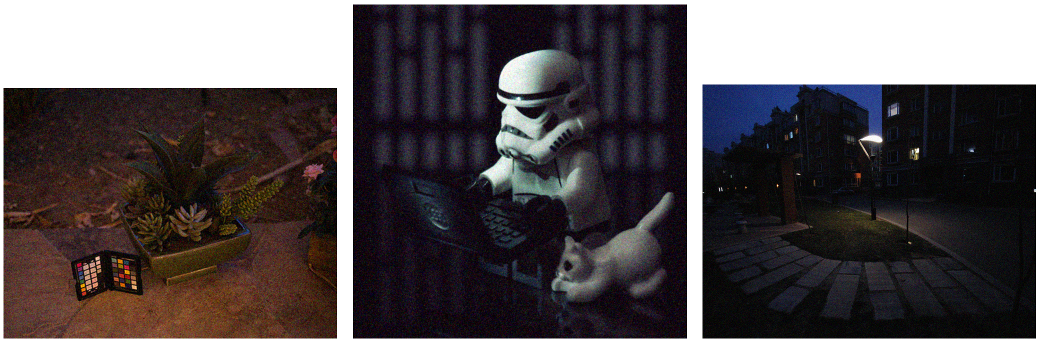
Fig 8: Images commonly used in other researches.

4 SIMULATION

4.1 Simulation condition

Images used in this experiment were taken by a digital camera Canon 5D mark IV, where ISO 12,800 and safe shutter speed were set. Because the ISO value was very high, the images contained a lot of noise. The images are shown in Fig 10a and Fig 11a.

In order to comparison of various methods, we also use some images set commonly used in other enhancement methods. In addition, to evaluate noise robustness against each enhancement method, noisy images were generated by adding Gaussian noise to the original ones shown in Fig 9



(a) (b) (c)

Fig 9: Adding noise to Fig 8.

The mean and variance of the noise were zero and 0.005, respectively.

In other words, we used three sets of images to compare each method.

1. Natural images which contain serious noise are taken by a digital camera as shown in Fig 7.

2. Images commonly used in other researches as shown in Fig 8.

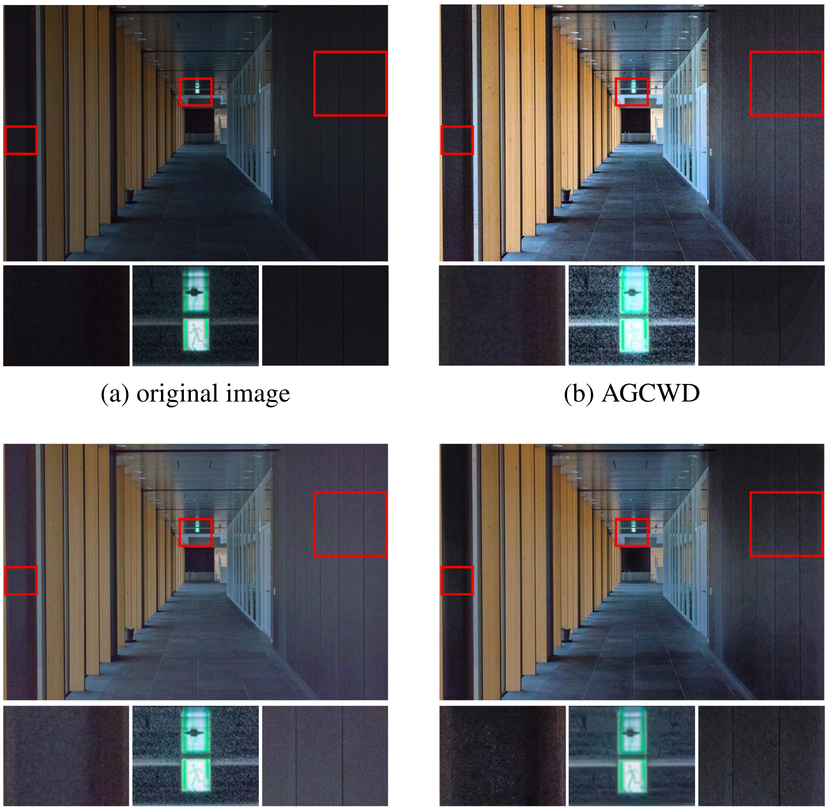
3. Adding noise to images commonly used in other researches as shown in Fig 9.

We carried out simulations to compare the proposed method with conventional contrast enhancement methods, AGCWD [4] and WVM [25] and LLIE [14] for objective evaluation. The simulations were run on a PC with Intel(R) Core (TM) i7 CPU (3.40GHz) and 8.00GB RAM running a Windows 10 OS and MATLAB 2018a. We adopted the $75th$ percentile as I_{th}.

4.2 Simulation results

4.2.1 Visual comparison

In visual comparison, Fig 10a and Fig 11a images were used as input images of each method. Next, we compared the resulting images, subjectively. The second columns are enlarged views of the previous column



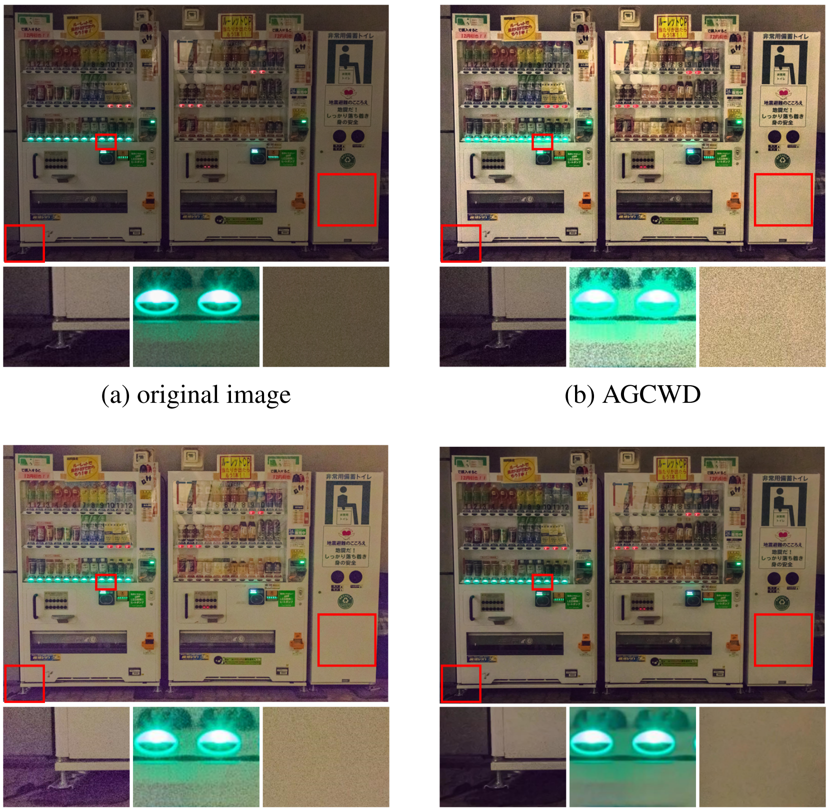
(a) original image (b) AGCWD

(c) WVM (d) Proposed method

Fig 10: Experimental Results under different contrast enhancement methods.

of red box, so that we can see the difference in dark and bright area, also noise. From Fig 10b, it is confirmed that AGCWD clearly reproduces dark areas and over-emphasizes bright areas. Further, we can see noise everywhere, obviously and we found a significant moire pattern in Fig 10b. The same situation occurred in Fig 11b. Besides, WVM not only enhanced noise, but also white balance was changed in dark area. Also, we easily observed the unusual purple area in Fig 10c and Fig 11c. By comparison the proposed method almost the same as the original image in bright areas and did not have a moire pattern in dark areas in Fig 10d and Fig 11d.

Over-enhancement can be found in the face of toy from and the street lights in the Fig 12b. Compared with other results, Fig. 12c has a slightly

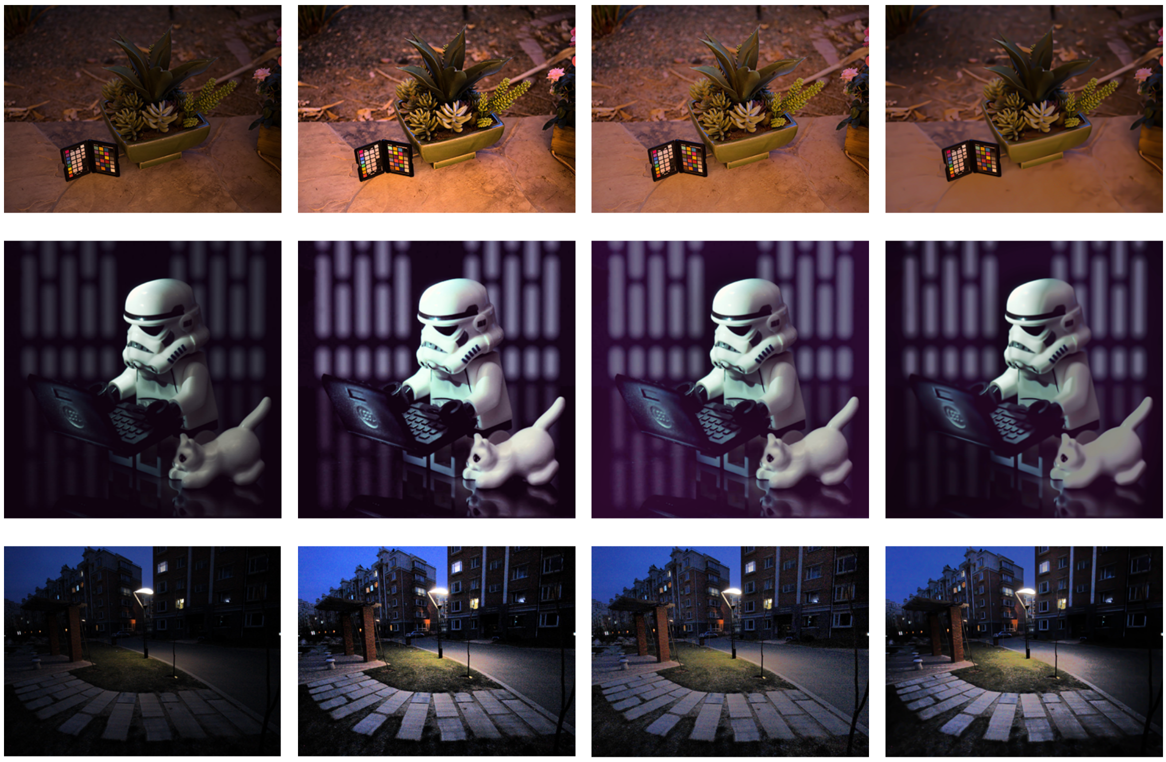


(a) original image (b) AGCWD (c) WVM (d) Proposed method

Fig 11: Experimental Results under different contrast enhancement methods.

lower contrast and can be seen from that the toy's head is also over-enhancement. Although the over-enhancement in Fig. 12d is not obvious, we can find that the texture details of the ground have been erased from the first image.

Because we don't know the noise situation of the original image in Fig. 12a, we added the Gaussian noise to the Fig. 12a and simulated again to know the robust of noise under each method. AGCWD and WVM enhanced noise, especially in the second column of images in the Fig. 9. Under the influence of noise, the over-enhancement of WVM seemed less obvious, but the over-enhancement of AGCWD still occurred. Noisy image enhanced by proposed method had almost the same noise level as the Fig. 13a, and had good performance in bright areas and dark areas. To



(a) original image (b) AGCWD (c) WVM (d) Proposed method

Fig 12: Experimental Results under different contrast enhancement methods with Fig 8.

sum up, the proposed method has a better balance between bright areas, dark areas and noise.

4.2.2 Objective evaluation

A blind image quality assessment called natural image quality evaluator (NIQE) [34] was used to evaluate the enhanced results. The lower NIQE value represents a higher image quality. As shown in Table 1, our method had a lower value.

Since NIQE is just for the naturalness of image assessment, we used another color image assessment called autoregressive- based image sharpness metric (ARISM) [35]. In Table I, the proposed method had a lower average on NIQE/ARISM than the other state-of-art methods, so that our

(a) original image (b) AGCWD (c) WVM (d) Proposed method

Fig 13: Experimental Results under different contrast enhancement methods with Fig 9.

method is shown to have a good balance and performance in most cases.

We evaluated both NIQE and ARISM of Fig. 12 and Fig. 13, and compared them with the average value as shown in Table 2. According to NIQE in Table 2, our proposed method did not perform very well in Fig. 12, and AGCWD presented better values. This is because the noise level of the original image is not high, and the brightness of the image is one of the key factors affecting NIQE. On the other hand, we can see that values of NIQE under severe noise, except for the proposed method, the image quality has declined in Fig 13. Considering the degree of NIQE decline, the proposed method is helpful to improve the image quality for the image under severe noise conditions. From ARISM in Table 2, we can see that the proposed method can slightly improve sharpness and color in Fig.

表 1: OBJECTIVE EVALUATION FOR NOISY IMAGES TAKEN BY CAMERA

Method		Original	AGCWD [4]	WVM [25]	LLIE [14]	Proposed method
NIQE	Fig. 10	6.4461	3.5778	3.1326	4.8199	**2.3404**
	Fig. 11	6.0844	4.1112	2.3942	3.3062	**2.8319**
ARISM	Fig. 10	3.1113	2.9589	2.8021	2.9979	**2.8233**
	Fig. 11	3.1875	3.1194	2.8897	2.8689	**2.6851**

表 2: OBJECTIVE EVALUATION FOR NOISY IMAGES

Method		Original	AGCWD [4]	WVM [25]	LLIE [14]	Proposed nethod
NIQE	Fig. 12	3.6181	3.1825	3.3002	3.6369	**4.2108**
	Fig. 13	12.5316	13.8919	13.3353	13.7193	**6.6031**
ARISM	Fig. 12	2.8304	2.9245	2.9011	2.9609	**2.6782**
	Fig. 13	3.9001	4.3099	3.7764	3.9761	**4.9521**

12. Compared with other enhancement methods, the proposed method is the only one that can improve the sharpness and color of the image. However, under the serious noise environment, the proposed method is inferior to other enhancement methods. Taken together, our proposed method performed better than Gaussian noise in terms of noise generated by digital cameras.

Fig 14 illustrated the results of the mapping curve with each method of Fig 10. In the dark areas, WVM was too much enhanced. In bright areas, AGCWD was over-enhanced so it did not preserve details. In contrast, our proposed method prevented noise amplification in dark areas and preserved more details in bright areas.

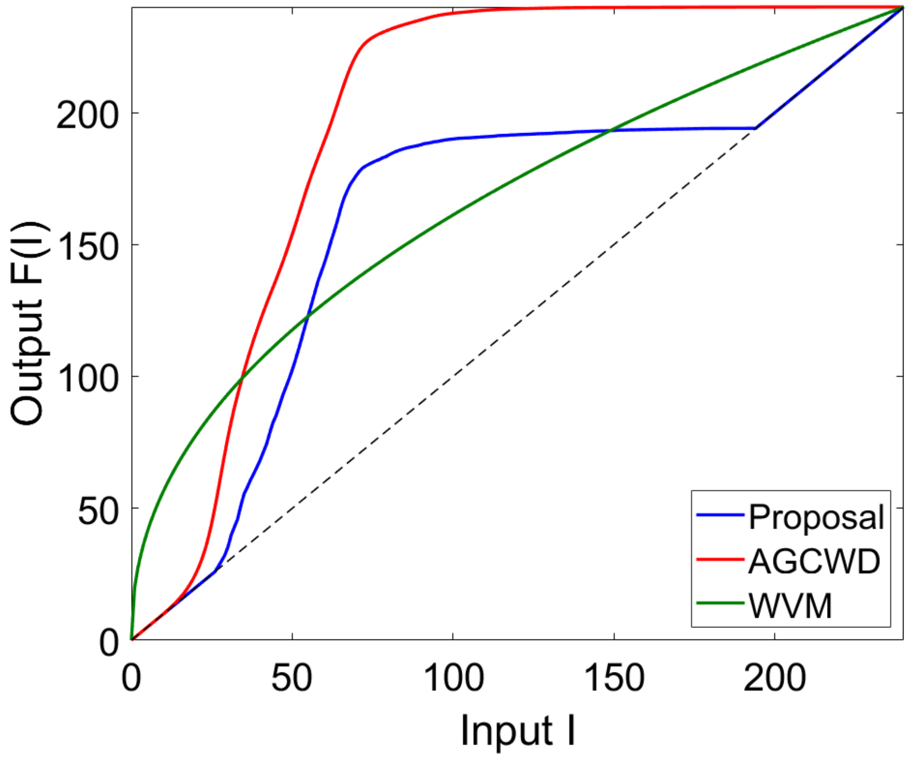


Fig 14: Mapping curves examples for the image in Fig 10.

5 Conclusion

In this paper, we have proposed a novel image contrast enhancement method based on a noise aware shadow-up function. We simulated different types of images to confirm the performance of the proposed method. The proposed method can enhance image contrast without over-enhancement and noise amplification. To prevent over-enhancement, the proposed method utilizes a shadow-up function. In addition, not only the use of noise aware histogram enables us to avoid amplifying noise, but also Retinex theory overcome the image enhancement is weak when images include strong noise. Experimental results showed that the proposed method successfully enhances contrast, while preserving details of highlight regions and suppressing some noise in dark regions.

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